PICSC FINAL REPORT

1. Administrative

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2. Public Summary

There is a broad consensus within the scientific community that global climate is undergoing a comparatively rapid change. Since many plants and animals depend on specific types of climate, it is imperative to understand: 1) the details of species' climatic preferences; 2) how climates may change in the future; and 3) how species may respond to these changes. Species distribution modeling (SDM) is an increasingly important tool to address conservation biology and global change issues. As Fortini and colleagues described in their largest vulnerability assessment in the US, SDMs provide critical information on biological refuges and potential future shifts in species ranges. In addition, climate changes could alter not only range, but abundance and capacity to persist. Whereas explicit spatial habitat models typically project occurrence, here we generate species models of abundance projected in response to environmental predictors.

This project gathers together over 35 years of data from thousands of locations in Hawaiʻi where vegetation was surveyed recording the details of all plant species found at each site. This permitted us to relate characteristics of the vegetation to specific aspects of the climate (in terms of rainfall and temperature, for example) that can be derived from detailed climate maps. We exclude highly invaded plots for the native species models, whereas agricultural and urban areas are included in the modeling to show pre-development scenarios. We have focused on ten important native and five important invasive plant species (mostly trees) in order to understand the characteristics of each species' preferred climatic habitat. Species were selected based on their ecological "importance" in communities, as well as on how much field data was available to analyze for this study. Colleagues at University of Hawaiʻi at Mānoa, USGS, NOAA, and other agencies are simultaneously researching how climate is changing and producing maps of projected future climate. Using these climate projections, and the relationships we have drawn about each species' preferences, we then produce estimates of where species' best habitat may be in the future. For native species, this is important because these areas may be key locations to focus conservation efforts, especially since many unique animals depend on native vegetation. For invasive species, these projections provide managers a powerful tool with which to target areas for control before invasive species are able to move into new habitats (and potentially disrupt natural ecosystem processes). To that end, we also examine characteristics of species growth rates and how their fruits/seeds are dispersed in order to understand how quickly they may be able to respond to changing climates and potentially move into newly emerging habitat. Together, the present and future habitat maps, and the ecological characteristics of our focal species provide an initial set of supporting tools for managers and decision makers.

3. Technical Summary

We compiled over 35 years of quantitative vegetation records from over 5,000 locations, representing a considerable proportion of the overall climate variability in Hawaiʻi. We exclude highly invaded plots for the native species models to reduce covariate effects, whereas agricultural and urban areas are included in the modeling to show pre-development scenarios. We developed novel correlative species abundance models using statistical

methods, quantitative vegetation plot data, environmental variables, and regional downscaled climate models to identify trends and estimate baseline and future projected shifts in the distribution and abundance of key native and invasive plant species in the Hawaiian Islands. We utilized these models to evaluate baseline conditions for each species and to forecast changes to community structure through expected shifts in species abundance. Models can be combined in order to predict community dominance, for example, by identifying the most abundant native species at a given location. This can be applied to: 1) spatial and temporal assessments of habitat quality and community structure comparisons; 2) defining specific ecological restoration objectives; and 3) identifying potential for key invasive species to threaten a site (even where they are presently not found). Future projected abundances can enhance conservation planning both by anticipating where native species may increase or decrease in abundance and by identifying areas where invasive species may extend their range. Combining this with assessments of relative response rates can aid managers in prioritizing native species to promote and invasive species to preemptively control at a given site.

4. Purpose and Objectives

Climate change is emerging as a central issue in conservation. The goal of this study is to utilize a vast array of quantitative vegetation plot data to model dominant vegetation composition. With varying accuracy, approaches in species response modeling can be used to define and predict a theorized realized niche of organisms and project shifts in future climate scenarios (Vorsino et al. 2014). Realized niche is the actual niche that a species occupies while in competition with other species. Whereas explicit spatial habitat models typically predict probability of occurrence, here we generate species models of abundance projected in response to environmental predictors. Species abundance models can be applied to multiple climate scenarios ranging from current to future climate scenarios derived from regional downscaling efforts.

A recent vulnerability analysis for all Hawaiian plants (Fortini et al. 2013) focused on the current and future climatic envelopes of each species (i.e. the general area within which each is found). However, this study elucidated the need for greater detail in three important ways. First, whereas spatial habitat models typically define areas most likely to support a given species, there is a clear need for species-specific models of abundance for important components of native vegetation. Hawaiian vegetation is unusual in that most ecologically important species are present across a wide range of physical environments, but vary greatly in local abundance, largely driven by climate. Second, many native species are directly threatened by key established invasive plant species, which displace native plants. Invasion affects animal species by degrading native-dominated habitats on which they depend. Third, the previous vulnerability assessment focused on spatial characteristics of present and future climatic habitat, however, species may respond to climate change at different rates due to ecological characteristics, such as dispersal rate, growth rate, and seedling survivorship. These differences could lead to unexpected consequences, such as faster and facilitated invasion of non-natives in changing habitats.

Understanding community structure in terms of abundance would greatly enhance our ability to evaluate the implications of climate change for a wide range of organisms and to evaluate changes to ecosystem processes. We have, therefore, developed a process to address these needs by focusing on the climatic and ecological characteristics of a select group of important native and invasive species. Our main objective is to generate species-specific models of estimated percent cover in relation to several independent variables (rainfall, temperature, substrate age) for both baseline and future (~2100) climate scenarios. These models cover the entire landscape of the Hawaiian islands, utilizing ecological data collected across the entire landscape. Our secondary objective is to assess growth, reproductive, and dispersal rates of focal species to inform the rates of different species transitions in concert with the objectives of an ongoing second phase of the comprehensive plant vulnerability analysis (Fortini et al., in development). These correlative species abundance approaches can be important tools in conservation management to delineate high priority areas, project changes to species responses in non-analog climates, and inform actionable science.

5. Organization and Approach
5.1. Vegetation data

We collated terrestrial vegetation plot data from the Hawaiian Islands from numerous sources. Final datasets represent true abundance (quantified as percent cover) with true absence at 5,000 locations for survey years from 1976-2014 in order to include sufficient amounts of data. The timeframe represents a baseline for late 20th / early 21st century conditions under the assumption that climate change did not strongly influence abundances of long-lived tree and shrub species during that period. Supplemental data was collected where large data gaps occurred, for example, in lowland dry and mesic forests and at high elevation. We integrated datasets with different

experimental design and methods in order to produce a data set representing a consistent concept of both estimated cover and (importantly) verifiable species absences. An assumption in SDM approaches is a state of equilibrium for species with their environmental predictors. For invasive models, we selected species that were established over 70 years, although establishment dates vary by island. We produced spatial species abundance models (SAMs) of potential vegetation cover (as percent) for 15 individual plant species of trees, shrubs and ferns, 10 native and 5 invasive (Table 1), under baseline and future (~2100) climate scenarios. This resulted in 30 models.

Table 1. Response characteristics of focal species. Higher values indicate a higher rate of response.

	Growth form	Seed/spore density (per unit cover)	Dispersal ability (per seed/spore)	Seedling germination and survival	Overall growth rate
Native species					
Acacia koa	Tree	3	2	4	4
Cheirodendron trigynum	Tree	4	4	4	3
Cibotium spp.	Fern	5	5	4	2
Dicranopteris linearis	Fern	5	5	3	3
Diospyros sandwicensis	Tree	3	4	1	1
Dodonaea viscosa	Tree	4	3	3	3
Leptecophylla tameiameiae	Shrub / Tree	4	4	2	1
Metrosideros polymorpha	Tree	5	5	2	1
Myoporum sandwicense	Tree	3	3	3	2
Sophora chrysophylla	Tree	3	1	3	3
Invasive species					
Clidemia hirta	Shrub	5	5	5	5
Grevillea robusta	Tree	4	4	5	4
Psidium cattleianum	Tree	4	4	5	4
Psidium guajava	Tree	3	3	4	4
Schinus terebinthifolius	Tree	4	4	5	3

5.2. Environmental data

We compiled parametric Geographic Information Systems (GIS) environmental grid layers including surface temperature, seasonal rainfall, topography, and geology. For baseline climate condition variables, we used temperature and rainfall estimates developed by Giambelluca et al. (2013) with grid cell resolution of 250m. To estimate climate change responses in trial runs, in collaboration with our PICSC working groups, we attempted to use both statistical downscaling of rainfall changes based on Coupled Model Inter-comparison Project 5 (CMIP5) for mid-century (Elison Timm et al. 2015), and dynamical downscaling of climate changes based on CMIP3 Special Report on Emissions Scenarios (SRES) A1B for end of century (based on Zhang et al. 2012; International Pacific Research Center). The CMIP3 scenario A1B includes an emission pathway far below than recent emissions, meaning if current trends continue, our future projections would be rather conservative. As such, new future forcings scenarios were developed to replace SRES; CMIP5 Representative Concentration Pathways (RCPs) are designed to cover a wider range of possible magnitudes of climate change in models (Collins et al. 2013).

We minimized the number of predictors by considering only those expected to be of high relevance across species. Final models incorporate four predictors with matching climate variables based on CMIP3 A1B for end of century (Zhang et al. 2012; International Pacific Research Center): simplified pioneer substrate (developed from geology maps by Price et al. (2012)) as a proxy for primary succession, mean annual temperature (MAT; bio1), wet season rainfall (bio18), and dry season rainfall (bio19). Environmental variables were resampled to a consistent projection (geographic WGS1984) with 250m grid cell resolution.

5.3. Species Abundance Models

In trial runs, we developed correlative species abundance models (SAM) using seven modeling methods including: boosted regression trees (BRT), generalized linear model (GLM), linear model (LM), multivariate adaptive regression splines (MARS), generalized additive model (GAM), and random forests (RF), implemented in R software (ver 3.2.0; R Core Development Team 2015). We first used default parameters in all approaches, and further explored custom parameters in BRT and GLM. Because commonly used species distribution modeling

(SDM) R packages are currently designed for modeling presence / absence only, we manually developed approaches using R. After additional preliminary analyses we also declined to use VisTrails (a platform for species habitat modeling).

When modeling species distributions, poor model fit may be due to various reasons, including: inappropriate modeling methods, missing data, missing covariates, heterogeneity, over-dispersion, and zero-inflation. We took several steps to minimize the impact of these factors on model performance. We examined data distribution and data gaps, and correlations between variables were assessed using a Pearson correlation coefficient. To estimate relative importance of predictors, we used species-specific response curves and variable importance plots. Individual model fit was assessed using residuals against fitted values plots, null and residual deviance values, and model comparisons using relative Akaike information criterion (AIC). We examined predictive performance of modeling approaches by first using 10 fold cross-validation (Lu et al. 2011; Barker et al. 2014), then using the area under curve (AUC) of the receiver operating characteristic (ROC), which evaluates model accuracy and discrimination by combining trade-off between the false positive proportion (Fielding and Bell 1997; Crase et al. 2015) and sensitivity (the true positive proportion) with R package pROC.

We discontinued RF, GAM, LM, and MARS approaches due to initial over or under-fitting in trials. BRT has major advantages in the ability to capture complex, non-linear response curves that are often more representative of species responses (Gaston 2003), automatically model multi-way interactions between explanatory variables, identify important relationships in large sets of predictor variables; and behave with insensitivity to outliers and transformations of the predictor variables (Elith et al. 2008; Barker et al. 2014). This has led to strong predictive performance of BRT models compared to other SDM modeling methods (Elith et al. 2006; 2008; Oppel et al. 2012; Barker et al. 2014; Crase et al. 2015). In trials, BRT performed strong to excellent in statistical evaluation metrics. By expert judgment, BRT appeared to overfit when allowed to consider higher model complexity, likely due to missing data and heterogeneity.

As an alternative to BRT, we explored GLM with and without variable interactions, 1st, 2nd and 3rd degree polynomials, and with response as continuous, multinomial, and categorical. Although GLM cannot accommodate non-linear response curves or complex interactions, we chose to use GLM since the simplistic model fitting allowed us to incorporate expert-based qualitative approaches by: 1) examining data issues; and 2) exploring, fine-tuning, and validating biological relevance of response-predictor relationships with expert judgment and quantitative evaluation statistics. We explored likely over-dispersion and zero-inflation of the data, however, adjusting our GLM models with poisson quasi-likelihood and zero-inflated models did not improve the model fit of species sampled. We compared negative binomial regression models as well (Potts and Elith 2006).

After hundreds of model iterations that considered different methods, model parameters, variable interactions, substrate categories, and multiple combinations of predictor variables, the model approach that best balanced model performance with low overfitting was a SAM based on a continuous second degree polynomial GLM model with second degree polynomial substrate variable removed, and no interactions. Using this approach, we produced final SAM current and future projections across the main Hawaiian Islands for all species. We used a 70/30 (train/test) random split using an evaluation data set that was independent of the training data, with 20 replicates. We did not further simplify species-specific models to preserve the same set of predictor variables for every model. Final maps show mean predicted abundance and standard deviation values which are calculated over 20 replicate models.

5.3.1. Model Validation

We examined the slope (m) and intercept (b) of the regression between predictions and observations for consistency, and direction and strength of bias in predictions, respectively. Several test statistics were used for validating model responses and a strong assessment of model performance. We calculated four evaluation statistics in R: AUC, Cohen's kappa, Pearson's chi-square goodness-of-fit Spearman rank correlation coefficient (ρ) and p-value, and Pearson's correlation coefficient (r) and p-value. For evaluating model accuracy, an AUC score of 0.5 is no better than random, above 0.7 may be considered fair, possibly above 0.8 as good, and above 0.9 is often considered excellent model performance (Swets 1988). However, comparisons of confidence intervals, partial AUC, sensitivity and specificity may reveal important weaknesses of high AUC values since definition of a good AUC value is relative and not absolute. High values of Spearman rank correlation (ρ) and Pearson's correlation coefficient (r) between predictions and observed values indicate overall consistency and strength of relationship. For final models in baseline climate conditions, we present AUC and Spearman rank correlation (ρ). With varying scales, Spearman rank correlation values 0.40-0.59 may be described as moderate, 0.60-0.79 as strong, and 0.80-1.0 may be considered very strong. Evaluation statistics are calculated over the 20 replicates and presented as mean ± one standard deviation.

5.3.2. Post-process

We calculated Spearman rank correlation (ρ) evaluation statistic for post-processed aggregation of observations and predictions into five community classes to compare performance with non-aggregated sets in R. To do so, we aggregated prediction grids into five equally sized regions to represent community classes, and calculated mean predicted abundance per class and mean abundance of independent test data per class.

For comparison, we used the coefficient of variation (CV), the ratio of standard deviation to mean predicted value in post-processing in ArcGIS 10.0 to remove areas of high uncertainty. We produced one map per species with the following process: 1) excluding areas with mean values below 1.0 due to inflated CV values of means near zero; 2) calculating CV; 3) assigned a no data value to areas where CV is comparatively high (greater than 0.1). To assess changes in potential abundance due to climate change, we calculated the projected net change in percent cover for each species by subtracting baseline values from projected future values. We also evaluated species abundances and net change by using a habitat quality layer (Price et al. 2012) as a mask to further identify areas of high conservation quality or high degradation in baseline climate conditions.

6. Project Results

6.1. Model Performance

Final SAMs varied in model performance between species and among validation metrics (Fig. 1). Of the 15 models, 14 had AUC values > 0.7 which may indicate fair performance in model accuracy. *Psidium guajava* had AUC < 0.7 indicating poor performance. Seven models with AUC > 0.8 had potentially good performance, and two models as excellent (AUC > 0.9; *Dodonaea viscosa* and *Cheirodendron trigynum*). Nine models had Spearman rank correlation (ρ) values > 0.42 which may indicate moderate strength of relationship (Fig. 1). Three models had Spearman (ρ) values > 0.60, with possibly strong relationships. No models had potentially very strong relationships (Spearman ρ > 0.80). High rates of uncertainty are prevalent with very high values of standard deviation in future predictions, but an increased number of model replicates may have reduced standard deviation values. Invasive species model performance did not appear to vary by potential equilibrium level (date of introduction as proxy), nor by number of non-zero presences.

Baseline climate models for *Vaccinium reticulatum* (AUC = 0.869 ± 0.082, ρ = 0.279 ± 0.047) showed possible good performance in AUC (accuracy) yet potentially weak performance in Spearman rank correlation (strength of relationship) and *Dodonaea viscosa* (AUC = 0.935 ± 0.065, ρ = 0.337 ± 0.45) showed possible excellent performance in AUC yet weak performance in Spearman rank correlation. *Dodonaea viscosa* performed well in distribution and abundance by expert ranking exercises, though areas with missing data were further identified. The baseline model for *Metrosideros polymorpha* (AUC = 0.874 ± 0.040, ρ = 0.700 ± 0.042) was more consistent, indicating good performance in AUC and strong performance in Spearman rank correlation. *Metrosideros polymorpha* showed strong performance in distribution but under-predicted abundance by expert ranking exercises. The baseline model for *Leptecophylla tameiameiae* showed fair performance in AUC but weak in Spearman rank correlation (AUC 0.711 ± 0.115, ρ = 0.373 ± 0.032). *Leptecophylla tameiameiae* performed well in distribution and abundance by expert ranking exercises.
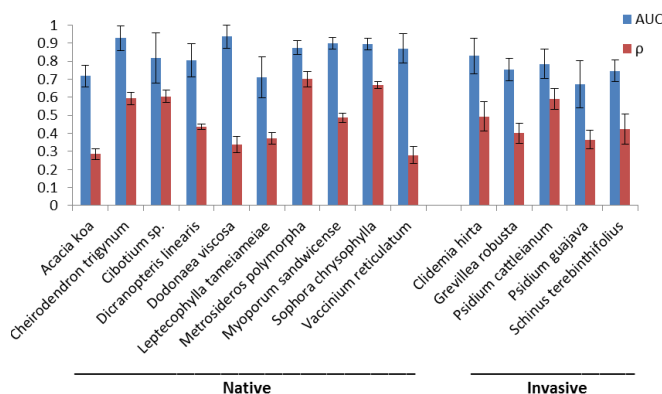

Figure 1. Plot representing SAM evaluation statistics, AUC and ρ mean values ± SD.

SAM performance was likely affected by the generalist rather than specialist niche characteristics of the species modeled. Research has shown that generalist species may be more difficult to predict; models for the generalist species had varying performances, poor evaluations, and inconsistent results compared with specialist species. This may be due to the capacity of generalists to persist in a wide range of environmental conditions not easily defined by data, independent variables or model design (Evangelista et al. 2008). Further, model performance for both native and invasive species (Fig. 1) was likely affected by the existence of large data gaps in key combinations of

predictor variables. Comparisons of goodness-of-fit (Spearman rank correlation) between non-aggregated and post-processed aggregated models generally showed small increases of performance with non-aggregated models.

6.2. Species Abundance Model Products

We produced 30 ensemble models of species-specific abundance (SAM) projections in baseline and future climate scenarios, with 30 accompanying standard deviation maps (Figs. 2-4). We post-processed 30 maps to illustrate areas of increased certainty, and calculated 15 net change maps. This resulted in 105 GeoTiffs as tools for conservation and resource managers and researchers.

7. Analysis and Findings

Correlative species abundance models are relatively new tools in conservation management, and this study developed several innovative approaches to enhance the modeling process by incorporating extensive expert judgment and vegetation data into method development and comparison and by examining effects of pre- and post-model aggregation on performance. However, we did identify several problems with this modeling approach that initially led to less realistic and reliable models. Examples of solutions to some of the problems we encountered include: collecting supplemental data in gap areas, reducing number of predictor variables to minimize correlation and increase biological relevance, removing confounding interactions, and reducing complexity of model fit to facilitate the examination and validation of response-predictor relationships. Further, we examined the performance of seven modeling approaches and the effect of resolution on projections.

In this first iteration, high variance of the data, inconsistent and generally weak GLM model statistical performance, and inconsistency with other data (such as vegetation maps) restricts the application of many of these models. The current availability of future climate projections limits consideration of potentially significant predictors, such as: cloud cover, fog interception, and wind velocity.

In baseline models, *Metrosideros polymorpha* had possibly good performance by AUC value, strong by Spearman rank correlation, and strong in distribution though generally low abundance by expert ranking exercises. *Cibotium spp.* had potentially good performance by AUC, strong by Spearman rank correlation, and strong in distribution and abundance by expert ranking exercises. Some species baseline models (for example, *Dicranopteris linearis*) performed poorly when evaluated using expert ranking exercises. Others, for example *Acacia koa*, had fair performance by AUC (accuracy), generally fit with the locations where the species is found, but under-estimated abundance as assessed from vegetation maps and satellite imagery. This may result from insufficient data from the areas where it is most abundant (montane mesic forest). Alternatively, this problem may stem from the somewhat disjunct distribution of the species: for example, despite the presence of seemingly

Figure 2. Projections of abundance of a key native tree species, *Metrosideros polymorpha*. Baseline conditions are shown both with and without a mask depicting where native vegetation (and therefore most *Metrosideros*) actually occur.

appropriate habitat, the species is absent from the Kohala Mountains on Hawai'i Island. Species from drier climates (at both low and high elevations) likely suffered from insufficient data availability, given that these habitats have been heavily impacted by increased wildfire and converted to invasive grassland. For example, our baseline model for *Sophora chrysophylla*, which dominates the highest elevations on older substrates just below tree line, projects high abundance in the summit region of Mauna Kea, despite the area being an alpine desert environment that supports little plant growth. This over-estimation in distribution may be due to the complete lack of vegetation plots at these altitudes (which would have added zero values and informed the model).
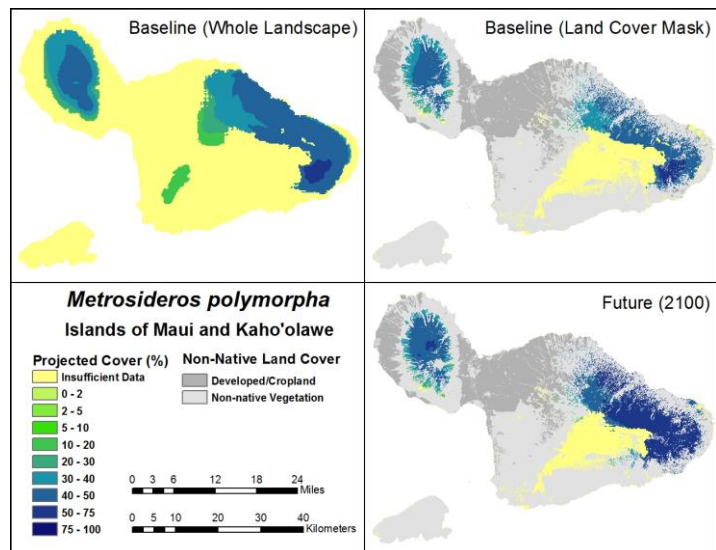
Despite these issues, a number of trends have emerged through assessment of the abundance models. First, increasing temperatures may promote the upslope expansion of some species (for example *Metrosideros*); however, other species (notably the lowland fern, *Dicranopteris linearis*) may increase in abundance with warmer temperatures at lower elevations. Many species from drier regions (*Myoporum sandwicense, Sophora chrysophylla*) may contract in range and abundance as high temperatures and drying combine to reduce their cover at their lowest elevations. Conversely, some invasive plants may expand their abundance in areas where they are presently scarce or absent. Taking these patterns together with present day land use, it is interesting to note that many of the lowest elevations are already in non-native dominated vegetation, such that, while future climates might otherwise cause them to decline, they are already largely absent.
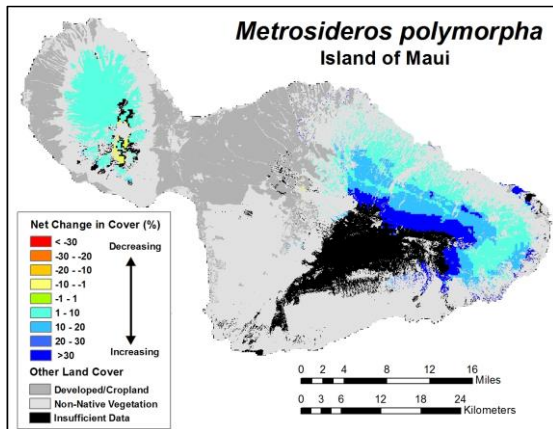

Figure 3. Net change in projected cover of *Metrosideros polymorpha*. Models suggest upslope expansion of the species in many areas. Lower elevation areas may become less favorable for the species, however, they are currently occupied by non-native vegetation. In such areas, it is difficult to separate the influences of climate change and invasive species.
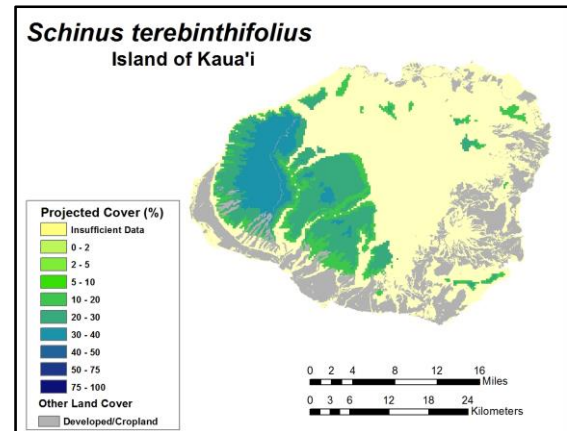
Figure 4. Projections of abundance of a key invasive tree species, *Schinus terebinthifolius* on Kauai. Note that for assessing this species, we have only masked out developed areas and cropland. This species has likely already achieved high cover values in non-native vegetation and has the potential to invade native vegetation in comparable climates. This therefore represents the "worst case scenario" needed by managers to assess degree and location of threat.

An important consideration of the models is that they project potential cover under equilibrium conditions (where species have had time to adjust to new climate conditions). In reality, species respond to climate change at different rates as a function of differences in their ecological characteristics. We, therefore, scored focal species on a relative scale to characterize different aspects of potential response to climate change. Each characteristic was scored on a 1 to 5 scale, with 1 contributing to a slow response and 5 contributing to a faster response; species may therefore have a high score in one characteristic and a low score in another for a distinct type of response (Table 1). While these properties undoubtedly vary spatially with climate, soil and other characteristics, estimates represent general characteristics within each species' range.

Response characteristics can be incorporated to inform land managers on expected relative rates of change. For example, *Metrosideros polymorpha* and *Leptecophylla tameiameiae* are estimated to have relative growth rates of 1 compared with 4 for *Psidium cattleianum* or 5 for *Clidemia hirta*, suggesting that even where they may disperse quickly enough, their growth may be outpaced by more competitive invasives. Conversely, where species with poor dispersal ability (e.g., *Sophora chrysophylla*) may fail to move into emerging habitat (Siefert et al. 2015), facilitated migration may be warranted. Overall, assessing the degree of intersection between native and invasive species in future climate scenarios can support management decision-making.

8. Conclusions and Recommendations

We have produced models broadly outlining the present and potential future distribution and abundance of key terrestrial plant species. Considering potential changes in the context of ecological characteristics for the species that were modeled, it is clear that many areas are likely to have invasive species increasing in abundance at the expense of natives. Nonetheless, the spatial resolution and inconsistent statistical performance of these models limits

their applicability. Further study, both in terms of filling field data gaps and more resolved climate projections will be essential to overcome these issues.

This study has highlighted several caveats to conducting and interpreting the results of climate change research in the Hawaiian Islands that apply broadly. Given the impacts of land use change and invasive species, very few native-dominated plots were available from low elevations and from drier areas. There was also a distinct lack of vegetation data from high elevation sites. As was the case with a recent modeling effort to identify the future threats of invasive plants (Vorsino et al. 2014), a shortage of data on invasive species locations, especially at low elevations, limits model performance in these environments. This is particularly problematic because future climates will include larger areas with warmer climates like those found in the lowlands at present. The limitations of the climate models themselves also warrant caution. Another field data shortfall was apparent in areas with steep topography. Very few of our plot data were from areas with greater than 20 degrees slope, despite the fact that about 10% of the total land area is on such steep slopes. Considering that both rare plant species and nesting seabirds depend on steep terrain, factoring in the influence of steep slopes on future habitat models will be crucial.

Empirically derived data on species response characteristics will also become increasingly important, and therefore field studies of growth and dispersal characteristics will support more nuanced understanding of species interactions. Finally, as with all climate change research, increases in accuracy of climatic predictions will enhance species response model accuracy. Importantly in Hawai'i, the effects of cloud cover, fog interception, and wind velocity could not be considered in this study, because reliable future climate variables were limited to temperature and precipitation. These factors strongly influence moisture demand (e.g., potential evapotranspiration), with profound effects on plant growth and survival independent of rainfall.

9. Management Applications and Products

The products of this effort include GIS layers of: 1) potential baseline and future abundance of 15 select ecologically "important" species; 2) net changes of species abundance from baseline to future climate scenarios; 3) pioneer substrate as a proxy for primary succession; and 4) habitat quality. An additional product is a table of response characteristics of the 15 focal species. Together, these products provide an initial set of supporting tools for managers and decision makers. However, given the inconsistency of their statistical performance, these exploratory abundance models should be used with caution and with reference to levels of uncertainty. As is the case with other macro-scale correlative models, they should be applied to management at a conceptual, landscape scale rather than for detailed management at local sites.

These models cover the entire landscape (including urban and agricultural areas), and therefore they can be applied in a variety of ways. For example, incipient invasive plants could be predicted to move into abandoned agricultural lands, with models providing guidance on where new threats might be expected. Abundance models could also serve as a guide for habitat restoration projects occurring where no nearby native vegetation is available as a reference. More likely however, these models will need to be considered within the context of present land cover and land use (i.e. which areas are presently developed or in agriculture, dominated by invasive species, or persisting native vegetation). Price et al. (2012) developed a key habitat status GIS layer that classifies the vegetation of the main Hawaiian Islands into these three basic types: dominated by native plants, dominated by alien plants but with native species, and heavily disturbed areas (agriculture, urban, etc.). This layer was used in our analysis and is being included with the other GIS products generated by this project.

By assessing the relative increases in potential cover of native species, managers may identify areas for native species restoration as the climatic habitat becomes more favorable in that specific location. Similarly, managers may employ the models to target areas for increased monitoring or control of invasive plants that are expected to expand into a given area. Together with consideration of response characteristics, these models can combine to promote multi-species landscape management in baseline and future climate scenarios to support ecosystem resilience.

10. Outreach

We have engaged in outreach in several venues as the project has advanced. At meetings of PICSC collaborators in July 2013, July 2014, and February 2015, we presented model approaches for pilot species. We presented these findings at the Hawaii Conservation Conference 2014, with an audience that included both managers and researchers. Postdoctoral researcher Tamara Wong participated in training in Colorado to explore the use of USGS SAHM Vistrails modeling methods in this project. PIs Price and Jacobi have met intermittently with various managers from both state and federal agencies and discussed the progress of this project. As a final dissemination of our key findings, we have scheduled a webinar for climate science centers and stakeholders for August 2015.

10.1. Publications
Wong, Tamara M., Jonathan P. Price, James D. Jacobi, and Lucas B. Fortini. (in prep) *Modeling Climate-Driven Changes to Dominant Vegetation in the Hawaiian Islands*. (Intended publication venue: USGS Open File Report Series).

Jonathan P. Price, Tamara M. Wong, James D. Jacobi, and Lucas B. Fortini (likely additional authors). (in prep) Spatial, Ecological, and Management Aspects of Climate-Change in the Hawaiian Islands. (Possible venues for publication: Global Change Biology, Landscape Ecology).

10.2. Presentations
Wong, T.M., J. Price, J. Jacobi. Adding to the Conservation Toolbox: Modeling Climate-Driven Changes to Dominant Hawaiian Vegetation. PICSC / PICCC Science Symposium. Honolulu, HI, USA. February 26-27, 2015.

Price, J., T.M. Wong, J. Jacobi. Applications for models of dominant vegetation in the Hawaiian Islands. PICSC / PICCC Science Symposium. Honolulu, HI, USA. February 26-27, 2015.

Jacobi, J. Developing the revised HI-GAP land cover map and Hawaiian Islands habitat quality map. Workshop on Regional Climate Change and Environmental Response in Hawaiʻi. Honolulu, HI, USA. July 22-23, 2014.

Wong, T.M., J. Price, J. Jacobi. Adding to the Conservation Toolbox: Modeling Climate-Driven Changes to Dominant Hawaiian Vegetation. Workshop on Regional Climate Change and Environmental Response in Hawaiʻi. Honolulu, HI, USA. July 22-23, 2014.

Wong, T.M., J. Price, J. Jacobi. Modeling Climate-Driven Changes to Dominant Hawaiian Vegetation. Hawaiʻi Conservation Conference. Honolulu, HI, USA. July 17, 2014.

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